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ARTIFICIAL NEURAL NETWORK BASED INTELLIGENT TEA TASTER-REVIEW

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Abstract. *Tea is the most favorable beverage in the world after the pure water. Professional tea tasters categorize the quality of the tea in subjective manner by assessing the several parameters. The flavor, aroma and color of tea are the most important and considered parameters when professional tea tasters categorize and evaluate tea. The value of above-mentioned parameters depends on the chemical composition of the tea. Basically, flavanols are major compounds which affect the quality of the tea. Therefore, it is possible to identify a correlation between flavanols composition of tea and professional tea taster's valuation. The main purpose of this article is identifying above correlation and according to that correlation design and implements "Artificial Neural Network (ANN) based Intelligent Tea Taster" to automate manual tea tasting process. This review is focused on training an artificial neural network according to identified correlation between flavanols composition and tea taster's valuation and based on that trained artificial neural network After going through successful training iterations and evaluations, a computer-based solution can be designed and implemented to define the quality of tea according to its flavanols compound. The results show good correlation of estimated values of theaflavins and thearubigins with the actual concentrations obtained by the system when we tested at laboratory. The review is based on ANN base Intelligent Tea Taster will automate the tea tasting process while improving efficiency, effectiveness and accuracy of the tea tasting process.*

Keywords: *Artificial Neural Network, Intelligent, Tea Taster, Flavanols*

Introduction

Tea tasting is the process of evaluating and assessing the quality, flavor, and overall characteristics of different types of tea. This can be done by a trained tea taster or by someone with a knowledge of tea and its flavor profiles (Lin et al., 2022). The process typically involves preparing the tea in a specific way, such as by brewing it with hot water at a specific temperature for a certain amount of time. The tea is then evaluated for its appearance, aroma, and taste, with attention paid to factors such as color, strength, and any nuances or complexities in the flavor (Zhang et al., 2020). Tea tasting can be used to identify the best tea leaves to use in blends, to evaluate teas for sale or to check the quality of tea after it has been packaged and stored (Fanshawe, 2021).

It is well known that tea is a unique beverage, but only few are aware of the factors which contribute to this uniqueness. Among these factors, the chemical composition of tea leaf is a very important factor that it is to say, tea leaf of unsuitable composition cannot be made into good tea (Negi et al., 2021). The expert professional tea tasters decide the quality of tea by performing subjective assessments on the brewed tea (Feng et al., 2019). In assessing the value of a tea, some of the properties which these experts take into consideration are color, aroma, and flavor of the liquor (Zhang et al., 2020). Each of these properties basically depends on one or more chemical compounds in brewed tea. It will also be evident from what follows that the standards of the expert professional tea tasters are closely related to the chemical composition of brewed tea (Jiang et al., 2019). The computer-based solution can be proposed to decide the taste of brewed tea if it is possible to find out correlation between chemical composition of brewed tea and professional tea taster's parameters (Gharibzahedi et al., 2022). This review will be focused on identifying correlation between biochemical composition of brewed tea and professional tea taster's parameters and proposed a computer solution, namely, "Artificial Neural Network based Intelligent Tea Taster" to define quality of the brewed teacup (Zhong et al., 2019). The automation system will improve effectiveness, efficiency and reliability of the tea tasting process.

Tea tasting with an Artificial Neural Network (ANN) is a process in which an ANN is trained to recognize and differentiate various types of tea based on their flavor profiles (Kimutai et al., 2020). This can be done by providing the ANN with a dataset of tea samples and their corresponding flavor attributes, such as astringency, sweetness, and aroma (Patil et al., 2021). The ANN then uses this information to learn the patterns and characteristics of different teas and can make predictions about the flavor profile of new tea samples (Liu et al., 2020).

This process can be useful for tea producers and sellers to improve their product quality and to identify potential new teas to offer their customers. The chemical composition of the tea is a major factor which affects the quality of tea. The quality of tea is defined by considering several parameters such as flavor, color and aroma of the brewed tea. The values of theses parameters can vary according to the variation of chemical compositions of brewed tea. Many attempts have been made in the past to identify the correlation between chemical composition and the quality of the tea but with little success (Teshome, 2019). There are specific chemical compounds which are directly affect to the quality of tea such as polyphenols, amino acids, carbohydrates, purines, organics acids, Caffeine, thebromine (Wu et al., 2019). Among these different groups of compounds, Polyphenols comprise the highest percentage to the flavor of the brewed tea (Kochman et al., 2020). Analysis of the Polyphenol fraction of the tea has indicated that it is made of several subgroups, including flavanols, flavonol glycosides, leucoanthocyanins, phenolic acids and depsides. Among these subgroups flavanols are the main compound which mainly affect to the taste of tea (Liu et al., 2020). Flavanols are made up of six catechins including catechin, Epicatechin, Gallocatechin, Epigallocatechin, Epicatechingallate and Epigallacotechin gallate. (Xu et al., 2021) Among those flavanols categories Catechin is the major compound which affects to the taste of the tea.

Presently this review article attempt has been made to identify whether correlation exists between flavanols compositions of tea and valuation of professional tea taster. According to the variation of flavanols compositions (specially catechin and theacatechin) the valuation of professional tea tasters can vary. Among these parameters, correlation can be identified and according to identified correlation computer-based solution can implement to define taste of tea when values of parameters are given, specially flavanols compositions of liquid tea and vapor of brewed tea and color scale in different flavanols compositions. The Primary objective of this review article is to identify the correlation between flavanols composition of brewed tea and valuation of professional tea taster, and based on identified correlation, design a computer-based software solution to automate manual tea tasting process. To fulfill this main objective, there are several secondary objectives to accomplish.

Materials and Methods

In this experiment, each orthodox black tea sample (made tea) was divided into two portions. One. portion is used for analysis of theaflavins (TF) and thearubigins (TR) using spectrophotometric technique and the other portion is used to prepare the tea liquor for analysis using electronic vision system. The operational flowchart for the experimentation is shown in Figure 1.

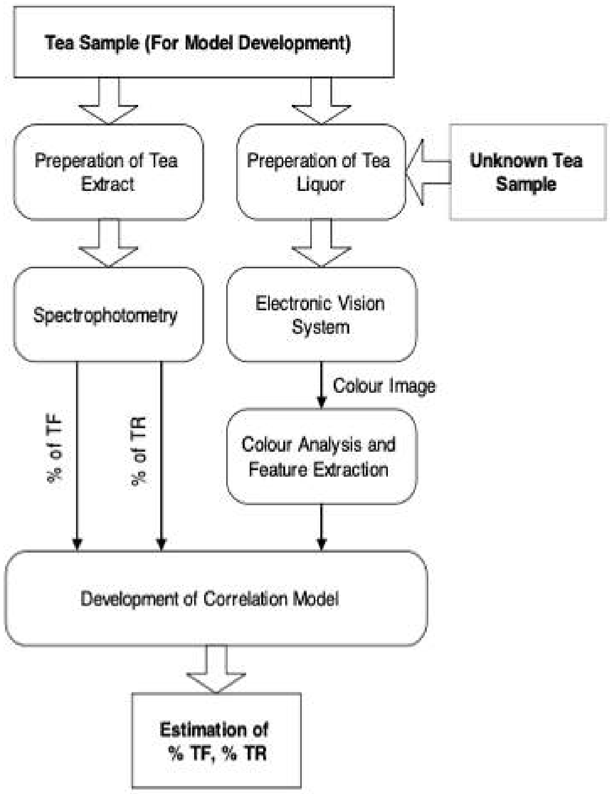

Figure 1: Operational Flow chart of the overall experiment

Sample collection

Two leaves and a bud shoot were harvested from tea bushes (*Camellia sinensis (L.) O. Kuntze*) of Chinary clone with a regular plucking interval of seven days produced at Lipton tea estate, Haputale, Sri Lanka. In this experiment, a total of 36 different tea samples had been used which were produced during the three flushing seasons - Early, Rains and Backend. These tea samples were prepared from good quality clone namely TRI 2023 and plucked between the month of April and July. The orthodox black tea samples were

processed at the Experimental Tea Factory. During processing, tea leaves were subjected to withering under ambient air at constant flow for 16-18 h; rolled using a 'peizy' roller for 0.5 h, fermented for 3 h, and dried with hot air at 95°C in a miniature dryer. 25 gm each of orthodox black tea sample, processed at different conditions in order to get wide variations in TF, TR parameters, were taken for experimentation. The TF and TR content of each orthodox black tea sample had been determined using spectrophotometry and presented to machine vision system for image analysis. The TF values obtained among 36 samples varied from 0.354 to 0.635 with an average of 0.504 and standard deviation of 0.078. On the other hand, TR ranges obtained were 3.015 to 5.421 with an average of 3.84 and standard deviation of 0.78 which indicates the wider variation in the TR values. Also, the samples were presented to a tea taster to grade the sample based on quality score ranging
from 1 to 10.

Estimation of theaflavins and thearubigins using spectrophotometry

Theaflavins and thearubigins were analyzed from tea infusion, prepared with boiling water. Absorbance/Optical Density (OD) of test solutions was measured on a Shimadzu ® UV-2450 UV-Vis spectrophotometer. Estimation of theaflavins and thearubigins was first developed by Ullah (Ouyang et al., 2019; Ullah, 2018).

Preparation of tea extract for TF and TR analysis

Each black tea sample was extracted in triplicate for the determination of the thearubigin fractions following the method described in Association of official Analytical Chemists (AOAC) (Baur and Ensminger, 1977). To determine TF and TR, 50 mL of the cool, well-shaken and filtered standard tea infusion were mixed with 50 mL of ethyl acetate.

First: Preparation of Solution A: A 4 mL portion of the ethyl acetate layer was taken and made up to 25 mL with methanol. Second: Preparation of Solution B: 25 mL of the remaining initial ethyl acetate layer were partitioned with 25 mL of 2.5% aqueous sodium hydrogen carbonate and the aqueous layer is discarded. A 4 ml portion of the washed ethyl acetate layer was made up to 25 ml with methanol. Third: Preparation of Solution C: 2 mL of saturated oxalic acid aqueous solution and 6 ml of water were added to a 2 mL portion of the aqueous layer left from the first extraction with ethyl acetate and diluted to 25 ml with methanol. Fourth: Preparation of blank sample is done similarly as stated above without mixing the tea extract. Fifth: Measurement of Absorbance: The absorbance of solutions A, B and C at 380 nm was obtained using a UV-VIS spectrophotometer-2450, Shimadzu ® against blank (Ullah, 2018; Baur and Ensminger, 1977).

Calculation of TF & TR from absorbance reading

Calculation of TF and TR value using spectrophotometry is obtained using equation (1) and (2) Baur and Ensminger, 1977(Ullah, 2018; Baur and Ensminger, 1977).

Equation(1)

E1 = Absorbance of Solution A at 380 nm after setting the reference point of the instrument using blank.

$$\%TF = 2.25 \cdot E_1$$

$$\%TR = \frac{[375*0.02*6.25(AC + AA - AB)]}{} [0.733*9*(WDM/100)]$$

Equation (2)

AA= Absorbance of solution A at 380 nm after setting the reference point of the instrument using blank
AB= Absorbance of solution B at 380 nm setting the reference point of the instrument using blank
AC= Absorbance of solution C at 380 nm setting the reference point of the instrument using blank.
WDM= Weight in gm of dry matter (5 gm)

C. The Machine Vision Set up

The Machine Vision System (Figure. 2) consists of the following elements:

Lighting arrangement

For image acquisition, samples are illuminated using four high intensity white DOME LEDs (equivalent to D65 standard light source). Four LEDs are arranged as a square configuration, 35 cm above the sample. The light intensity inside the enclosed cabinet is measured using a light sensor (silicon based), mounted at one corner of the sample holder. A separate light intensity controller constantly compares the sensor output to the preset signal level and changes the power supply output to keep the light intensity constant irrespective of power supply voltage and any variation due to aging, ensuring uniform illumination on the system tray where tea liquor cup is placed in the predefined slot.

Digital camera for image acquisition

A low cost, colour digital camera, model C905 (Logitech ®) is located vertically over the sample at a distance of 30 cm. The angle between the camera lens and the lighting source axis is approximately 45 degree. The camera is interfaced with PC/ laptop using Universal Serial Bus (USB2.0) communication. To avoid the varying ambient illumination conditions, the entire system is placed inside a cabinet whose internal surface is painted. Images are taken using the following camera settings: manual mode, manually adjusted fixed focus, no zoom, no flash with resolution of 640x480 (N x M) pixels and storage in 24 bit BMP format. The white balance of the camera is set in auto mode.

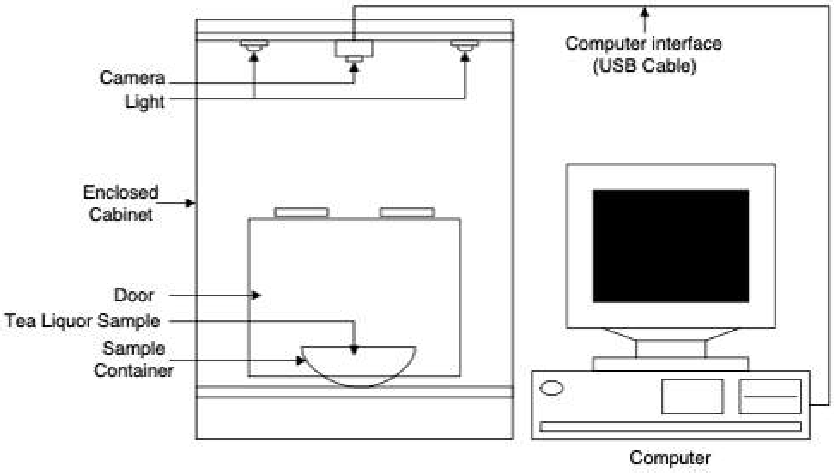

Figure 2: Schematic diagram of Electronic Vision System

Colorimetric Measurement

The Tea color was measured both subjectively and objective in each trial. The tea is filled in white cups were rated hedonically (1 = poor; 5 = excellent) for color quality by a panel of six panelists familiar with tea. Color measurements were made periodically with a Minolta (Model CR-300, Ramsey, N.Y., USA) on color and taste of tea using the CIELAB color parameters. L*, a*, and b*. Each measurement was taken at three locations for each sample. A standard white calibration plate was employed to calibrate the equipment. Results were then converted into browning value (browning index (BI)), defined as brown color purity, which is usually used as an indicator of browning in sugar-containing food products (Bernard et al., 2020). The following equation was used to determine BI:

$$BI = (x - 0.31) \times 100 / 0.172$$

where x is the chromaticity coordinate calculated from the XYZ tristimulus, values according to the following formula $x = X/(X+Y+Z)$.

Artificial Neural Networks

An artificial neural network (ANN) is an interconnected group of artificial neurons simulating the thinking process of human brain. ANNs are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below (Figure 3). There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target.

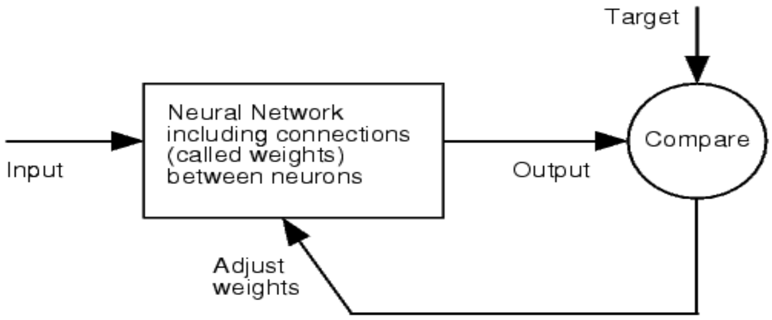

Figure 3. Neural network training

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. An ANN can create its own organization or representation of the information it receives during learning time. So we can consider ANN as a magical black box trained to achieve expected intelligent process, against the input and output information stream.

An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. Probabilistic neural networks can be used for classification problems. A "probabilistic" neural network (PNN) is the name given to a radial basis function network modified for classification purposes.

Probabilistic Neural Networks

Probabilistic Neural network is derived from Radial Basis Function (RBF) network which is an ANN using RBF. RBF is a bell shape function that scales the variable nonlinearly. PNN estimate the probability density function for each class based on the training samples. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities and produces a 1 for that class and 0 for the other classes. The PNN trains immediately but execution time is slow, and it requires a large amount of space in memory. It really, only works for classifying data. The training set must be a thorough representation of the data. Probabilistic neural networks handle data that has spikes and points outside the norm better than other neural nets. Probabilistic networks perform classification where the target variable is categorical. PNN has been employed in the proposed scheme because of its fast-training speed and simple structure. Network structure of the proposed system, which is a Probabilistic Neural Network, is illustrated in Figure 4.

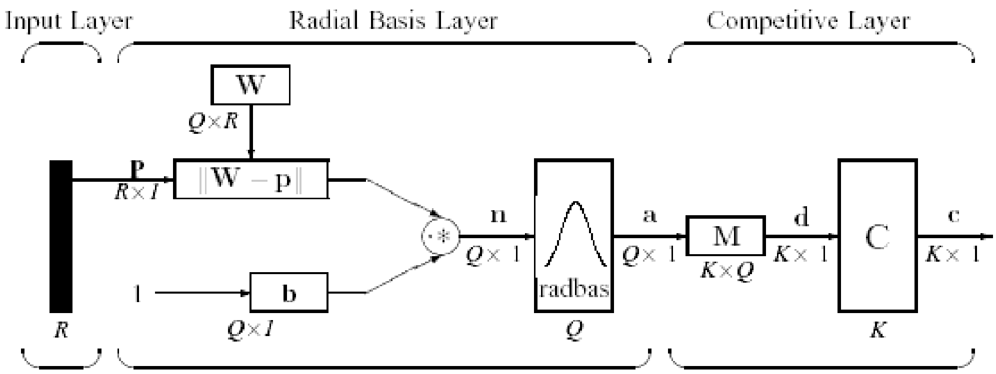

Figure 4. Network structure.

Results and Discussion

Artificial neural network (ANN) using multi-layer perceptrons often exceeds the performance of other function approximators for arbitrary, complex and nonlinear input-output mappings. The performance of the following artificial neural network framework has been considered.

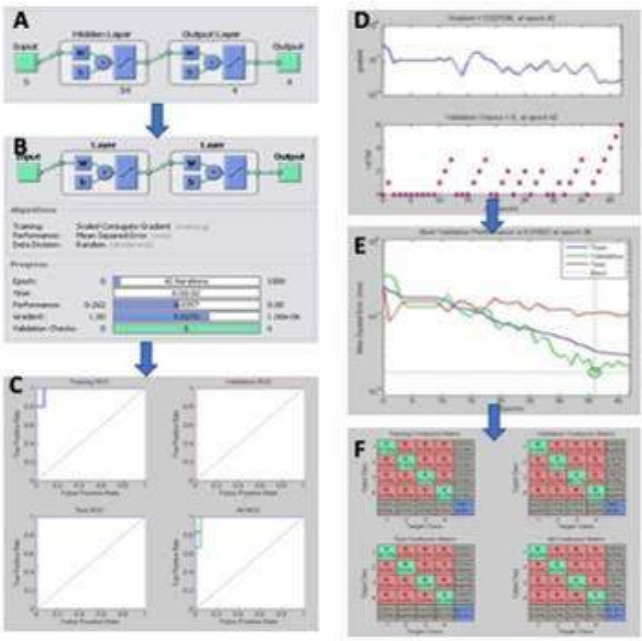

Figure 5- Artificial Neural Network analysis. A - Trained Neural Network structure; B- Trained Neural Network results; C- Operating Characteristic; D- Training Status; E- Performance; F- Confusion Matrix

Experiments were carried out under standard laboratory conditions with 36 tea samples using developed electronic vision system for this review article. The image of the liquor was taken five times for each sample. Thus, 180 images were captured and the images were analyzed using an image analysis program for initial processing followed by feature extraction. Finally, the data analyses were performed using MATLAB. The flow is shown in Figure 5 and Fig 5A and 5B shows about the ANN working flow.

The quality scores of tea samples considered in this study was given by tea tasters are plotted against the concentrations of TF and TR in Fig. 5C, 5D and 5E. A positive correlation between Tea Tasters' score with TF and TR values has been clearly observed. Thus the proposed methodology for the approximate estimation of TF and TR contents can give a fair idea about the quality of Tea. Error rate was observed and it was minmal (Figure 5F).

System Testing & Evaluation

Testing was done in three steps. Image processing segment and Neural network segment were tested separately and the system was tested as the final step.

Testing the Image Processing Segment

Table 1 shows the results for IM testing. Accuracy rate is 95%.

Table 1: Test scenarios for IM Processing

Tea Sample	Expected results				Actual Results			
	W	L	A	P	W	L	A	P
DSC00995.JPG	980	2474	5180579	21712	980	2474	5180580	21710
DSC00996.JPG	896	2444	1384842	20894	896	2444	1384840	20890
DSC00998.JPG	709	2190	1059613	21970	709	2190	1059610	21970
DSC00999.JPG	735	2371	1158688	19141	735	2371	1158680	19140
DSC01001.JPG	788	2332	1207093	19868	788	2332	1207090	19870
DSC01003.JPG	856	2296	1291313	19505	856	2296	1291310	19500

Testing the NN

Table 2 shows the results of NN testing and 70% of accuracy rate was obtained.

Table 2: Test scenarios for NN Training

Inputs	Expected result	Actual result
2.524489796 2094.009297 5286.305102 238.6044123 0.138153939	1 0 0 0	0.8543 0.2333 0.0126 0.3654
1.858974359 948.0719828 1762.441506 104.6745824 0.062623568	0 1 0 0	0.0186 0.6547 0.1642 0.0943
2.841584158 432.7691638 1229.75 51.88439246 0.034058845	0 0 1 0	0.3721 0.2759 0.5452 0.1857
2.583690987 662.6740033 1712.14485 79.92181709 0.050322118	0 0 0 1	0.6975 0.2376 0.2758 0.7235

Conclusion

Theaflavins and Thearubigins are two very important chemical constituents for the formation of tea liquor colour and brightness and the estimation of these chemical constituents gives a fair idea about the quality of orthodox black tea. In this paper, an electronic vision system using low cost digital camera and illumination set up has been described to estimate the TF and TR content. ANN is gives the best solution to replace the tea taster with machine learning. Image of liquor sample is directly captured by the camera and image analysis techniques have been employed for extraction of different colour features. All in all, the proposed electronic vision method promises a new and rapid method for quality analysis of orthodox black tea by facilitating instant estimation of important bio-chemical compounds of tea.

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